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**Project Title: Hyperspectral Image Classification for Crop Detection**

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Course Name: Minor Project - I

Course Code: 15B19CI591

Program: B. Tech. CS&E

3rd Year 5th Sem

**2024 – 2025**

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**Introduction**

Hyperspectral imaging is a rapidly emerging remote sensing technology that captures image data at numerous wavelengths across the electromagnetic spectrum. Unlike conventional imaging systems that record data in three broad bands (red, green, and blue), hyperspectral sensors collect detailed spectral information at hundreds of narrow, contiguous bands. This capability enables the precise identification of materials and subtle differences in surface properties, making it an invaluable tool for agricultural applications.

In the context of crop detection, hyperspectral imaging offers significant advantages. Crops exhibit distinct spectral signatures based on their physiological and biochemical properties. These signatures can be exploited to differentiate between various crop types, assess plant health, and monitor growth stages. The ability to accurately classify crops not only aids in precision agriculture but also supports sustainable farming practices by enabling efficient resource management, early disease detection, and targeted intervention.

This project focuses on leveraging hyperspectral image classification to detect and classify crops. The objective is to develop an efficient, memory-safe, and robust model capable of processing high-dimensional hyperspectral data. The methodology encompasses several key steps, starting with data pre-processing, which includes dimensionality reduction using Incremental Principal Component Analysis (PCA) and feature scaling. By reducing the data dimensions while preserving essential spectral information, the project minimizes computational complexity and enhances model performance.

The classification model implemented in this project is based on a lightweight convolutional neural network (CNN), referred to as LightweightSANet. This network is designed with a series of convolutional, batch normalization, and pooling layers that extract spatial and spectral features from hyperspectral patches. A final classifier, composed of fully connected layers, maps these features to crop categories. The design prioritizes both accuracy and computational efficiency, ensuring that the model is well-suited for real-world applications where processing resources may be limited.

Training and testing procedures are carefully crafted to address challenges such as class imbalance and overfitting. The training process incorporates data augmentation techniques like horizontal and vertical flipping to enhance model robustness. Additionally, the use of gradient accumulation and adaptive learning rate scheduling further refines the training process, ensuring optimal convergence. On the testing front, the model’s predictions are used to generate a comprehensive classification map that visually represents crop distribution across the study area.

In summary, this project not only demonstrates the potential of hyperspectral image classification in crop detection but also contributes to the broader field of precision agriculture. By integrating advanced machine learning techniques with sophisticated data processing strategies, the approach aims to deliver accurate, efficient, and scalable solutions for modern agricultural challenges.

**Problem Statement**

Accurate crop detection is essential for precision agriculture, yet traditional remote sensing techniques often struggle with the inherent complexities of hyperspectral data. Hyperspectral imaging provides a wealth of spectral information across hundreds of narrow bands, resulting in high-dimensional datasets that are both computationally intensive and prone to noise. This project addresses the challenge of efficiently processing and classifying such data to accurately identify and monitor various crop types.

One of the primary challenges is managing the high dimensionality of hyperspectral images. The abundance of spectral bands, while providing detailed information, can lead to redundant features and increased computational costs. To mitigate this, the project employs dimensionality reduction techniques such as Incremental Principal Component Analysis (PCA). However, selecting the optimal number of principal components to retain essential spectral signatures while discarding irrelevant information remains a delicate balance.

Another significant issue is the imbalance in class distribution inherent in agricultural datasets. Certain crop types may be underrepresented, which can skew model performance and lead to biased predictions. Addressing this involves carefully crafted training strategies, including data augmentation and the use of class-weighted loss functions, to ensure that minority classes are adequately represented during the learning process.

Furthermore, the spatial variability in hyperspectral images necessitates a model that can effectively extract both spatial and spectral features. Traditional machine learning models often fall short in capturing these complex relationships. The project, therefore, proposes a lightweight convolutional neural network (CNN) architecture—LightweightSANet—that is specifically designed to handle these challenges while maintaining computational efficiency. This model integrates techniques such as gradient accumulation and adaptive learning rate scheduling to overcome issues related to overfitting and to enhance convergence.

In summary, the problem addressed in this project involves developing an effective methodology for hyperspectral image classification to facilitate crop detection. The focus is on overcoming challenges related to high-dimensional data processing, class imbalance, and the extraction of meaningful spatial-spectral features, ultimately aiming to provide an efficient and scalable solution for modern precision agriculture.

**Background Study**

Hyperspectral imaging has emerged as a transformative technology in remote sensing, providing detailed spectral information across hundreds of contiguous bands. This wealth of spectral data enables precise material identification and discrimination, which is particularly valuable in agricultural applications where subtle differences in crop characteristics are crucial for accurate detection and classification.

Recent research in the field has focused on developing sophisticated deep learning models to address the challenges posed by the high dimensionality and inherent complexity of hyperspectral data. Two notable studies in this area include "SANet: A Self-Attention Network for Agricultural Hyperspectral Image Classification" and "Improved Transformer Net for Hyperspectral Image Classification." Both studies leverage advanced attention mechanisms to enhance feature extraction from hyperspectral images.

The SANet model introduces a self-attention mechanism tailored for hyperspectral data, allowing the network to selectively focus on the most informative spectral and spatial features. This targeted approach helps mitigate the curse of dimensionality by emphasizing critical information while suppressing noise and redundant features. As a result, SANet demonstrates improved classification accuracy with a relatively lightweight architecture, making it well-suited for agricultural applications where computational resources may be limited.

Similarly, the Improved Transformer Net builds on the success of transformer architectures, which have revolutionized natural language processing, by adapting them for hyperspectral image classification. This model employs attention mechanisms that capture both global and local dependencies within the data. By doing so, it effectively integrates contextual information across different spectral bands and spatial locations, thereby enhancing the network’s ability to discriminate between various crop types. The transformer-based approach also addresses challenges related to feature redundancy and class imbalance, which are common in hyperspectral datasets.

These studies not only contribute to the theoretical understanding of hyperspectral image processing but also provide practical insights into designing robust, efficient models for real-world applications. Their methodologies inspire the development of more efficient architectures, such as the LightweightSANet proposed in this project, which seeks to balance performance with computational efficiency. The integration of techniques like Incremental PCA for dimensionality reduction and adaptive learning strategies further underscores the evolution of methodologies aimed at harnessing the full potential of hyperspectral data.

In summary, the background study of hyperspectral image classification reveals a dynamic research landscape where attention-based models play a pivotal role. The advancements demonstrated by SANet and the Improved Transformer Net serve as important benchmarks, guiding the design and implementation of new models for precise crop detection and contributing to the broader field of precision agriculture.

**Design Model**

This project integrates an efficient data preprocessing pipeline with a lightweight deep learning architecture to address hyperspectral image classification for crop detection. The model design is structured into distinct components that ensure effective feature extraction and classification while maintaining computational efficiency.

**Data Preprocessing and Feature Extraction:**

* Data Acquisition: Load the Indian Pines hyperspectral dataset along with corresponding ground truth labels.
* Patch Extraction: For each labeled pixel, extract a 13×13 patch and apply reflection-based padding at the edges to maintain consistent dimensions.
* Dimensionality Reduction: Use Incremental Principal Component Analysis (PCA) to reduce the number of spectral bands to 30, preserving significant spectral features while eliminating redundant data.
* Normalization: Apply a StandardScaler to the reduced data to standardize feature distributions, facilitating faster convergence during training.
* Memory-Efficient Processing: Execute the preprocessing tasks in manageable chunks to ensure the approach is scalable and memory-efficient.

**Model Architecture: LightweightSANet:**

* Convolutional Feature Extraction: The initial convolutional layer reduces the 30 PCA components to 8 channels, followed by batch normalization and ReLU activation; a max pooling layer is applied to condense the spatial information; a second convolutional layer increases the depth from 8 to 16 channels, further refining the feature set with additional normalization and non-linear activation.
* Adaptive Feature Aggregation: Use an adaptive average pooling layer to aggregate spatial features into a fixed-size representation, irrespective of the input dimensions.
* Classification Block: Flatten the pooled features and pass them through a fully connected network that includes a dropout layer to mitigate overfitting, followed by a final linear layer that maps the features to one of 16 crop classes.

**Training Strategy:**

* Data Augmentation: Enhance model robustness by performing on-the-fly data augmentation via random horizontal and vertical flips.
* Class Imbalance Handling: Incorporate class-weighted loss functions to address the skewed class distribution often present in agricultural datasets.
* Optimization Techniques: Implement gradient accumulation to simulate larger batch sizes on limited hardware and use an adaptive learning rate scheduler (ReduceLROnPlateau) to adjust the learning rate based on validation accuracy for efficient convergence.
* Model Checkpointing: Save the model’s best state—determined by the highest validation accuracy—for later testing and deployment.

**Testing and Evaluation:**

* Inference Pipeline: During testing, apply the same preprocessing (using saved PCA and scaler objects) to new data patches and aggregate the model’s predictions to create a comprehensive classification map that visually represents crop distribution.
* Performance Metrics: Evaluate the model based on overall accuracy and generate a detailed classification report, including precision, recall, and F1-score for each crop class.

This integrated design model efficiently addresses the challenges of high-dimensional hyperspectral data, ensuring accurate and computationally efficient crop detection for precision agriculture applications.

**Tools and Technology Used**

* **Programming Language:** Python was chosen for its robust ecosystem and extensive libraries, making it ideal for data processing, machine learning, and deep learning tasks.
* **Deep Learning Framework:** PyTorch is used to build and train the LightweightSANet architecture, offering dynamic computation graphs and flexibility for custom neural network layers, which support techniques such as data augmentation, gradient accumulation, and adaptive learning rate scheduling.
* **Data Preprocessing and Machine Learning Libraries:** scikit-learn is employed for Incremental PCA to reduce the dimensionality of hyperspectral data, StandardScaler to normalize feature distributions, train\_test\_split for creating balanced datasets, and compute\_class\_weight to address class imbalances. NumPy and SciPy complement these tasks by providing efficient numerical computations and tools for reading and processing MAT files containing hyperspectral data and ground truth labels.
* **Serialization and Object Persistence:** Joblib is used to save and load preprocessing objects such as the PCA and scaler models, ensuring reproducibility and reducing the need for repeated computations during testing.
* **Visualization and Evaluation:** Matplotlib generates visual outputs like classification maps to assess the spatial distribution of crop detections, while scikit-learn metrics (overall accuracy, precision, recall, and F1-score) provide a comprehensive evaluation of the model’s performance.
* **Development Environment and Supporting Tools:** Integrated development environments (IDEs) and version control systems are utilized to maintain code quality, facilitate efficient collaboration, and manage versioning throughout the project lifecycle.

This collection of tools and technologies forms an integrated ecosystem that supports every aspect of the project—from data preprocessing and feature extraction to model training, evaluation, and visualization—resulting in an efficient and scalable framework for hyperspectral image classification in crop detection.

**Implementation**

* **Data Loading**: Load the Indian Pines hyperspectral dataset and corresponding ground truth labels from MAT files using SciPy.
* **Patch Extraction**: Extract a 13×13 patch around each labeled pixel and apply reflection-based padding at the edges to maintain consistent dimensions.
* **Dimensionality Reduction**: Use Incremental Principal Component Analysis (PCA) to reduce the number of spectral bands to 30, preserving key spectral features.
* **Data Normalization**: Standardize the reduced data using StandardScaler for improved model convergence.
* **Dataset Splitting**: Split the processed data into training and testing sets using stratified sampling to ensure balanced class representation.
* **Data Augmentation**: Integrate on-the-fly augmentations via a memory-safe dataset class by applying random horizontal and vertical flips to enhance model robustness.
* **Model Architecture (LightweightSANet)**: Define the model in PyTorch with two convolutional blocks—the first reduces the 30 PCA components to 8 channels (followed by batch normalization, ReLU activation, and max pooling), and the second increases channels from 8 to 16 (with additional normalization and activation), followed by adaptive average pooling; finally, use a fully connected classifier with dropout to map the features to 16 crop classes.
* **Training Strategy**: Employ gradient accumulation to simulate larger batch sizes on limited hardware, use an adaptive learning rate scheduler (ReduceLROnPlateau) that adjusts based on validation accuracy, address class imbalance by incorporating computed class weights into the loss function, and save the best performing model checkpoint based on validation performance.
* **Testing and Inference**: Load the saved PCA and scaler objects to preprocess test data consistently, process test data in batches to predict crop classes, and aggregate results to construct a comprehensive classification map.
* **Evaluation**: Assess performance using overall accuracy and generate a detailed classification report including precision, recall, and F1-score for each crop class.

**Results and Evaluation**



